Situation Awareness & Decision-making for Autonomous Driving

Dr HDR Christian LAUGIER
Research Director at Inria & Scientific Advisor for Probayes and for Baidu China
Inria Chroma team & IRT Nanoelec
christian.laugier@inria.fr

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Technology status & Ongoing challenges for AVs

- Strong involvement of Car Industry & GAFAs + Large media coverage + Increasing Governments supports
- An expected market of 515 B€ at horizon 2035 (~17% world automobile market, Consulting agency AT Kearney, Dec 2017)
- But Legal & Regulation issues are still unclear ... idem for Technologies Validation & Certification issues!

=> Numerous experiments in real traffic conditions since 2010 (Disengagement reports, Hero lights to system maturity)

=> Still insufficient ... Realistic Simulation & Formal methods are also under development (eg. EU Enable-S3)

Tesla Autopilot L2 with Radar & Mobileye/Intel
Commercial ADAS product => Tested by millions

Drive Me trials (Volvo, 2015)
- 100 Test Vehicles in Gothenburg: 10,000 km, 70km/h
- No pedestrians & Separations between lanes

Waymo with EU projects in last 2 years: 3 months experience in Bordeaux & La Rochelle 2012 (Fr.)

Dense 3D mapping & Numerous vehicles 10 years R&D: 8 millions km covered since 2010 & 25 000 km/day

“Self-Driving Taxi Service L3” testing in US (Uber, Waymo) & Singapore (nuTonomy)

=> Autonomous Mobility Service; Numerous Sensors + “Safety driver” during testing (take over in case
=> Uber: System testing since 2017, Disengagement every 0.7 miles in 2017 (improved now)
=> Waymo: 1st US Self Driving Taxi Service launched in Phoenix in Dec 2018

Disengagement reports provide insights on the technology maturity

Several benign & serious accidents in past few years

Safety is still not guaranteed!
Fatal accidents involving AVs – Perception failure

- Tesla driver killed in a crash with Autopilot “level 2” active (ADAS mode) – May 2016
  - The Autopilot failed to detect a white moving truck, with a brightly lit sky (Camera Mobileye + Radar)
  - The human driver was not vigilant & didn’t take over

- Self-driving Uber L3 vehicle killed a woman
  => First fatal crash involving a pedestrian
  Temple, Arizona, March 2018
  - Despite the presence of multiple sensors (lidars, cameras …), the perception system failed to detect the pedestrian & didn’t disengaged
  - The Safety Driver reacted too lately (1s before the crash)

AVs have to face two main challenges

Challenge 1: The need for Robust, Self-diagnosing & Explainable Embedded Perception

Video Scenario:
- The Tesla perception system failed to detect the barriers blocking the left side route.
- The driver has to take over and steer the vehicle away from the blocked route (for avoiding the collision).
AVs have to face two main challenges

Challenge 2: The need for **Understandable Driving Decisions** *(share the road with human drivers)*

*Human drivers actions* are determined by a complex set of interdependent factors difficult to model *(e.g. intentions, perception, emotions ...)*

⇒ *Predicting human driver behaviors is inherently uncertain*

⇒ *AV have to reason about uncertain intentions of the surrounding vehicles*

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**Video scenario:**

- Scene observed by the dash cam of a *bus* moving behind the Waymo AV
- *Waymo AV* is blocked by an obstacle and it decides to execute a left lane change
- The *bus driver* misunderstood the Tesla’s intention and didn’t yield
- The two vehicles collided

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**Perception & Decision-making requirements for AVs**

**Dynamic Scene Understanding & Navigation Decisions**

- **Semantic Based Reasoning**
  - **Situation Awareness & Decision-making**
    - Sensing + Prior knowledge + Interpretation
    - Selecting appropriate Navigation strategy *(planning & control)*

**ADAS & Autonomous Driving**

- **Embedded Perception & Decision-making** for Safe Intentional Navigation

**Dealing with unexpected events**

- **Risk detection** & **Reflexive actions**
  - Anticipation & Risk Prediction required for avoiding an upcoming collision with “something”
    - High reactivity & reflexive actions
    - Focus of Attention & Sensing
    - Collision Risk estimation + Avoidance strategy

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**Main features**

- Dynamic & Open Environments ⇒ *Real-time processing & Reactivity* *(several reasoning levels are required)*
- Incompleteness & Uncertainty ⇒ *Appropriate Model & Algorithms* *(probabilistic approaches)*
- Sensors limitations (no sensor is perfect) ⇒ *Multi-Sensors Fusion*
- Hardware / Software integration ⇒ *Satisfying Embedded constraints*
- Human in the loop (mixed traffic) ⇒ **Human Aware Decision-making process** *(AI based technologies)*
  - Taking into account Interactions + Behaviors + Social rules *(including traffic rules)*
1st Paradigm: Embedded Bayesian Perception

Main challenges
- Noisy data, Incompleteness, Dynamicity, Discrete measurements
- Strong Embedded & Real time constraints

Our Approach: Embedded Bayesian Perception
- Reasoning about Uncertainty & Time window (Past & Future events)
- Improving robustness using Bayesian Sensors Fusion
- Interpreting the dynamic scene using Contextual & Semantic information
- Software & Hardware integration using GPU, Multicore, Microcontrollers...

Bayesian Perception: Basic idea

Multi-Sensors Observations
Lidar, Radar, Stereo camera, IMU...

Probabilistic Environment Model including Dynamics

Concept of “Dynamic Probabilistic Grid + Bayesian Filtering”
- Clear distinction between Static & Dynamic & Free components
- Occupancy & Velocity probabilities
- Designed for Highly Parallel Processing (to satisfy real-time constraints)
- Includes Embedded Models for Motion Prediction & Collision Risk Assessment
- Patented technology & Industrial licenses 2018 (Toyota, Easymile)

Main philosophy
Reasoning at the grid level as far as possible for both:
- Improving Efficiency & Reactivity to unexpected events => Highly parallel processing & High frequency!
- Avoiding most of traditional object level processing problems (e.g. detection errors, wrong data association...)

[PhD Thesis Coué 2005]
[Coué & Laugier IJRR 2005]
[Laugier et al ITSM 2011]
[Rummelhard et al ITSC 2015]
[Mooc uTOP 2015]
Dynamic Probabilistic Grid & Bayesian Filtering – Main Features

=> Exploiting the dynamic information for a better understanding of the scene

Main Features

Sensors data fusion
Bayesian Filtering
Extracted Motion Fields

Occupancy Grid
(Static part)
Free space
Static obstacles

Motion fields
(Dynamic part)
3 pedestrians
Moving car
2 pedestrians

Patented Improvements & Implementations (2015, 2017)

Grid & Pseudo-objects
Classification (using Deep Learning)

Detection & Tracking + Moving Objects Classification,
=> CMCDOT 2015 (including a “Dense Occupancy Tracker”)
Main challenges

- Uncertainty, Partial Knowledge, World changes, Real time
- Human in the loop + Unexpected events + Navigation Decision based on Perception & Prior Knowledge

Approach: Prediction + Risk Assessment + Bayesian Decision-making

- Reason about Uncertainty & Contextual Knowledge (using History & Prediction)
- Estimate Probabilistic Collision Risk at a given time horizon \( t+\delta \) (\( \delta \) = a few seconds ahead)
- Make Driving Decisions by taking into account the Predicted behavior of all the observed surrounding traffic participants (cars, cycles, pedestrians ...) & Social / Traffic rules

Decision-making: Two types of “collision risk” have to be considered

- Short-term collision risk \( \Rightarrow \) Imminent collisions with “something” (unclassified), time horizon <3s, conservative hypotheses
- Long-term collision risk \( \Rightarrow \) Future potential collisions, horizon >3s, Context + Semantics, Behavior models

Concept 1: Short-term collision risk (Basic idea)

\( \Rightarrow \) How to deal with unexpected & unclassified events (i.e., “something” is moving ahead)?
\( \Rightarrow \) Exploit previous observations for anticipating future objects motions & related potential future collision

Thanks to the prediction capability of the BOF technology, the Autonomous Vehicle “anticipates” the pedestrian motion and brakes (even if the pedestrian is temporarily hidden by the parked vehicle)
Short-term collision risk – Main Features & Results

=> Grid level & Conservative motion hypotheses (proximity perception)

- Main Features
  - Detect “Upcoming potential Collisions” a few seconds ahead (3-5s) in the Dynamic Grid
  - Risky situations are both localized in Space & Time (under conservative motion hypotheses)
  - Resulting information is used for choosing the most appropriate Collision Avoidance Maneuvers

- Experimental results
  - Crash scenario on test tracks
    - Almost all collisions predicted before the crash
    - Collision Risk Assessment (video 0:45)
      - Yellow => time to collision: 3s
      - Orange => time to collision: 2s
      - Red => time to collision: 1s

Concept 2: Long-term Collision Risk (Object level)

=> Increasing time horizon & complexity using Context & Semantics

=> Key concepts: Behaviors Modeling & Prediction + Traffic Participants Interactions

Decision-making in complex traffic situations

- Understand the current traffic situation & its likely evolution
- Evaluate the Risk of future collision by reasoning on traffic participants Behaviors
- Takes into account Context & Semantics

Context & Semantics

History + Space geometry + Traffic rules

Behavior Prediction & Interactions

For all surrounding traffic participants (using learned models)

Probabilistic Risk Assessment
Behavior-based Collision risk – Main approaches & Results

Trajectory prediction & Collision Risk

- Increased time horizon & complexity + Reasoning on Behaviors & Interactions

Intention & Expectation (Mixed Traffic & Interactions)

- Patents 2012 (Inria - Renault) & 2013 (Inria - Berkeley)

3rd Paradigm: Models improvements using Machine Learning

Perception level: Construct “Semantic Grids” using Bayesian Perception & DL

Decision-making level: Learn driving skills for Autonomous Driving

1st Step: Modeling Driver Behavior using Inverse Reinforcement Learning (IRL)

2nd Step: Predict motions of surrounding vehicles & Make Driving Decisions for Ego Vehicle
**Perception Level:** Semantic Grids (Bayesian Perception + DL)

**Objective:** *Add Semantic information* (cars, pedestrians, roads, buildings ...) in each cell of the Dynamic Occupancy Grid model, by exploiting *additional RGB inputs*.

**Approach:** *A new “Hybrid Sensor Fusion approach” combining Bayesian Perception & Deep Learning*

1. Semantic grid estimation with a Hybrid Bayesian and Deep Neural Network approach, Erkent et al., IEEE IROS 2018
2. Conditional Monte Carlo Dense Occupancy Tracker, Rummelhard et al., ITSC 2015

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Semantic Grids – Experimental Results & Current Work

Current Work

- Improve accuracy with more dense training datasets
- Implementation on embedded systems for real-time process
- Adaptation to bad weather conditions
- Panoptic segmentation & tracking

Decision-making level: Learning Driving Skills for AD

1st Step: Driver behavior modeling

[Sierra Gonzalez et al, ICRA 2018]

- Learn Model parameters from real driving demonstrations using Inverse Reinforcement Learning (IRL)
- Driver behaviors are modelled using a Cost function $C(s) = \sum_{i=1}^{K} w_i \cdot f_i(s)$ which is assumed linear on a set of K hand-crafted features (e.g. Lane index preferences, Deviation from desired velocity, Time-to-collision to frontal targets, Time-gap to rear targets …)
- A training set containing “interesting highway vehicle interactions” was constructed out of 20 minutes of highway driving data & used to automatically learn the balance between features. We are extending the approach using larger datasets and various traffic conditions.

=> Obtained models can be leverage to Predict human driver behaviors & Generate human-like plans for the ego vehicle (mandatory in mixed traffic)

Comparison between demonstrated behavior in test set & behavior induced by the learned model
**Decision-making level: Learning Driving Skills for AD**

**2nd Step: Motion Prediction & Driving Decisions**

- A realistic Human-like Driver Model can be exploited to predict the long-term evolution (10s and beyond) of traffic scenes [Sierra Gonzalez et al., ITSC 2016]

- For the short/mid-term, both the Driver model and the Dynamics of the target provide useful information to determine future driving behaviors

=> Our probabilistic model fuses Model-based Predictions & Dynamic evidence to produce robust lane change intention estimations in highway scenes [Sierra Gonzalez et al., ICRA 2017]

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**Experimental Vehicles & Connected Perception Units**

- Toyota Lexus
- Renault Zoé

**Connected Perception Unit (V2X communication)**

*Same embedded perception systems than in vehicles*

=> Exchanging only relevant information (e.g. Risk parameters)

**Experimental Vehicles & Connected Perception Units**

- Experimental Vehicles
- Connected Perception Units (V2X communication)
- Same embedded perception systems than in vehicles
- => Exchanging only relevant information (e.g. Risk parameters)

**Experimental Vehicles & Connected Perception Units**

- Toyota Lexus
- Renault Zoé

**Connected Perception Unit (V2X communication)**

*Same embedded perception systems than in vehicles*

=> Exchanging only relevant information (e.g. Risk parameters)
Experimental Areas

- **Protected experimental area** => *Testing Autonomous Driving L3 & L4*
  - Crash test track
  - Connected Perception Unit

- **Open real traffic (Urban & Highway)** => *Testing Autonomous Driving L2 (ADAS)*

Summary & On going work

- **Autonomous Driving in various Traffic & Context situations (cooperation with industry)**
  - Various Dynamics & Motion constraints & Contexts
  - Adapted “Collision Risk” & “Collision avoidance maneuvers” (Risk & Maneuver characterization)
  - Cooperation IRT Nanoelec, Renault, Iveco ...

- **Embedded & Extended “Semantic Grids”**
  - Embedded “Semantic Grids” & “Panoptic Segmentation”
  - Improved scene understanding (various weather conditions)
  - Cooperation Toyota
  - 1 Patent & 3 publications (IROS’18, ICARCV’18, Unmanned System journal 2019)

- **Autonomous Driving in mixed traffic (Prediction & Planning) using learned models**
  - Driver Behavior modeling using Driving dataset & Inverse Reinforcement Learning => *Human-like Driver Model (for mixed traffic)*
  - Motion Prediction & Driving Decision-making for AD performed by combining “learned Driver models” & “Dynamic evidences”
  - Cooperation Toyota
Thank You